Science of the Total Environment 624 (2018) 790–806

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Spatio-temporal variations in climate, primary productivity and efficiency of water and carbon use of the land cover types in Sudan and Ethiopia

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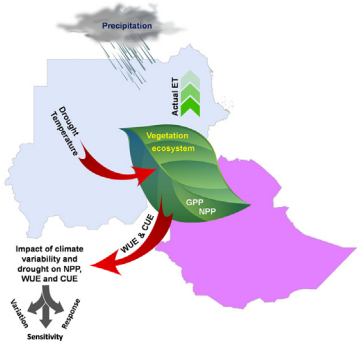
HIGHLIGHTS

- Interaction between climate and vegetation ecosystems is complex and still unclear.
- Correlating climate variability and vegetation productivity provides useful insights.
- Spatio-temporal variations in climate, NPP, WUE and CUE using remote sensing data
- NPP, WUE and CUE vary widely among land covers in different climate conditions.
- This variation should be considered in policy-making for water and food security.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 9 October 2017
Received in revised form 7 December 2017
Accepted 7 December 2017
Available online 27 December 2017

Editor: D. Barcelo

Keywords:
Net Primary Productivity
Remote sensing
Climate variability
Water use efficiency
Carbon use efficiency
Drought

ABSTRACT

The impact of climate variability on the Net Primary Productivity (NPP) of different land cover types and the reaction of NPP to drought conditions are still unclear, especially in Sub-Saharan Africa. This research utilizes public-domain data for the period 2000 through 2013 to analyze these aspects for several land cover types in Sudan and Ethiopia, as examples of data-scarce countries. Spatio-temporal variation in NPP, water use efficiency (WUE) and carbon use efficiency (CUE) for several land covers were correlated with variations in precipitation, temperature and drought at different time scales, i.e. 1, 3, 6 and 12 months using Standardized Precipitation Evapotranspiration Index (SPEI) datasets. WUE and CUE were estimated as the ratios of NPP to actual evapotranspiration and NPP to Gross Primary Productivity (GPP), respectively. Results of this study revealed that NPP, WUE and CUE of the different land cover types in Ethiopia have higher magnitudes than their counterparts in Sudan. Moreover, they exhibit higher sensitivity to drought and variation in precipitation. Whereas savannah represents the most sensitive land cover to drought, croplands and permanent wetlands are the least sensitive ones. The inter-annual variation in NPP, WUE and CUE in Ethiopia is likely to be driven by a drought of time scale of three months. No statistically significant correlation was found for Sudan between the inter-annual variations in these indicators with drought at any of the time scales considered in the study. Our findings are useful from the view point of both food security for a growing population and mitigation to climate change as discussed in the present study.

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https://doi.org/10.1016/j.scitotenv.2017.12.090
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1. Introduction

Net Primary Productivity (NPP) is defined as the amount of atmospheric carbon that is captured by plants and transformed into biomass (Zhao and Running, 2010). The total amount corresponding to the photosynthesis process is called Gross Primary Productivity (GPP). The difference between NPP and GPP is referred to as respiration (Ardö, 2015), which is the amount of carbon previously assimilated by the plant and subsequently used for maintenance of the biomass or for growth. Monitoring of the variability in primary production is critical due to the fact that NPP provides vital services for human survival (Ardö, 2015). Reduction in NPP potentially jeopardizes food security and may increase global warming since a reduction in NPP might decrease the available carbon sinks (Zhao and Running, 2010). Whereas the spatial variation of NPP depends on vegetation type, soil, climate conditions and human activities, the temporal variation of NPP depends mostly on the variability of climatic factors (Li et al., 2016). Several climate factors control the NPP, such as temperature, precipitation and shortwave solar radiation (Li et al., 2016). Temperature and precipitation have more influence on NPP in arid and semi-arid areas whereas solar radiation is the main controlling factor in humid and semi-humid areas (Liu et al., 2015). Temperature plays a role in raising NPP (Zhao and Running, 2010). Although the period from 2000 through 2009 was the warmest decade in the records since 1880 (NOAA, 2016), Zhao and Running (2010) found that global NPP has declined by 0.55 petagram carbon (Pg C) during the same decade. They suggested that a drying trend in the southern hemisphere was the main driver for this reduction. There has been a debate regarding these findings as to whether there was a decrease in NPP or whether this decrease was due to artifacts from the applied model (Samanta et al., 2011; Zhao and Running, 2011). If NPP is affected by climate as suggested in that model; then, NPP should have decreased during this period (Medlyn, 2011).

Ecosystems differ in their responses to climate variability (Knapp and Smith, 2001). Different plant species respond differently to drought conditions based on their physiological and structural characteristics in order to prevent loss of water (Van Der Molen et al., 2011). Understanding how land cover types respond to drought and to climate variability can promote more efficient management of these land covers and can, in turn, assist significantly in securing water and food in the future.

Many studies have been conducted on this matter, yet most of them have focused on the climate driver of the NPP variation on a global scale (e.g. Huang et al., 2016; Liu et al., 2015). Recent analyses showed that semi-arid areas are a main control of global NPP variations (Huang et al., 2016; Ahlström et al., 2015). However, it is important to examine whether the same pattern of NPP found by Zhao and Running (2010) on a global scale also applies on regional and local scales (Chen et al., 2013). As the scaling of the relevant processes is typically non-linear, different patterns are likely to emerge at the regional or local scale. Drought is expected to be more severe in the future (Ault et al., 2014). Therefore, it is important to investigate the effect of drought on primary productivity and efficiency of the land cover types in terms of water and carbon use. Analysis of these interactions at regional and national levels is useful and provides essential information for land cover management and climate policy-making (Peng et al., 2017; Liu et al., 2015). Recently, a country-scale analysis of the relationship between NPP and drought was published by Peng et al. (2017). The data used in their work were Moderate Resolution Imaging Spectroradiometer (MODIS) NPP and the drought Standardized Precipitation Evapotranspiration Index (SPEI). They found that countries show different trends in NPP for the period 2000 to 2014, and only 35 countries accounted for >90% of the global NPP.

On the continental scale, Africa has witnessed an increase in NPP during the same period, i.e. from 2000 through 2009, by 0.189 Pg C. This was mostly due to a decrease in vapor pressure deficit (Zhao and Running, 2010). African ecosystems produce around 20% of the total global NPP (Ciais et al., 2011), and a large fraction of the inter-annual variability in the global carbon cycle is due to ecological processes on the African continent (Williams et al., 2007). Monitoring the variation in vegetation productivity, WUE and CUE, and correlating this variation with climate variability for large areas is a challenge, particularly against the backdrop of the given limitations of ground data, especially in the countries of Sub-Saharan Africa, for instance, where ground weather stations are few and sparsely distributed.

WUE and CUE are useful indicators for the assessment of the pattern of water use and carbon sequestration by plants. WUE is defined as "The rate of carbon uptake per unit of water lost" (Tang et al., 2014). It can be calculated by different approaches according to the purpose of investigation (Ito and Inatomi, 2012). Here, WUE is defined as the amount of water evaporated for every g carbon/m^2 of NPP produced, i.e. NPP/ET_a, where ET_a is the actual evapotranspiration (Kuglitsch et al., 2008). CUE is defined as a ratio of NPP to GPP. The earliest conception of the CUE is that it ideally equals 0.5 (DeLucia et al., 2007; Zhang et al., 2009). However, CUE should not be considered as a constant value since the driving processes of photosynthesis and respiration are nonlinearly governed by different environmental drivers; thus, the ratio of these fluxes varies. Photosynthesis and respiration are primarily governed by the absorbed photosynthetically active radiation (APAR) and temperature, respectively. Several researchers noted that CUE might vary depending on climate factors (e.g. precipitation and temperature) and geographical location (Zhang et al., 2009). Plants are considered carbon sinks. Examining the variability of CUE is thus important for climate change and CO_2 emissions studies (Chen et al., 2013). Also, a better understanding of WUE and CUE may lead to a better management of ecosystems (Tang et al., 2014; Zhang et al., 2009).

Variability in primary productivity affects food availability and food security. At the same time, the magnitude of primary production strongly affects the carbon cycle (Zhao et al., 2005). However, lack of continuous ground observation hinders the long-term analysis of the dynamics of vegetation development. Luckily, many remote sensing or model based public-domain data sources nowadays provide continuous spatial climate observations and other key environmental variables (e.g. LAI, biomass, soil moisture). The general availability of these public-domain data sources provides a unique opportunity for examining the climate-plant productivity relationship, which is essential for a reproducible analysis of the impact of climate variation on primary productivity. However, in comparison with climatic variables, only few public-domain databases provide data on primary productivity. MODIS data, such as the primary productivity (MOD17) product, are often used to detect the variability of primary productivity as well as analyzing the WUE and CUE of land cover types or entire ecosystems and their association with climate conditions. For a summary of the most important studies, refer to Table 1.

To the best of our knowledge, apart from the study of Peng et al. (2017) who studied the impact of drought on NPP on a country scale for the whole globe, no other study was conducted to analyze the response of NPP, WUE and CUE of different land cover types to drought and climate variability in Sub-Saharan Africa based upon generally available datasets. In this study, inter-annual variations in climate conditions and drought on different time scales for the period from 2000 through 2013 were correlated with inter-annual variation in NPP, WUE and CUE in various land cover types in Sudan and Ethiopia. The two selected countries are examples of Sub-Saharan countries with severe data-scarcity and high vulnerability to climate variation and food insecurity. Understanding the spatio-temporal variability of NPP, WUE, and CUE is essential to achieve a better land management in these countries and to improve food security.

2. Materials and data

2.1. Study area and its importance

East Africa is one of the most challenging areas for managing natural resources due to many factors. It is a region highly vulnerable to climate

Table 1
Review of some research using MOD17 data of NPP and GPP.

Author(s)	Scale	Time period	Main objective(s)	Main findings
Huang et al., 2016	Global	2000–2013	To examine the impact of drought on NPP	NPP is highly controlled by drought, and semi-arid ecosystems play the most important role in the inter-annual variability on the global scale.
Li et al., 2016	Global	2000–2014	To study the climate factors affecting NPP variability and feedback of this variability on actual evapotranspiration (ET_o).	NPP is correlated positively with ET_o, and it responds differently in the northern and southern hemispheres according to dominant climate factors in each hemisphere.
Ahlström et al., 2015	Global		To figure out the role of semi-arid ecosystems in the trend and variability of land CO_2 sinks.	The trend and variability of the global land CO_2 sinks are largely derived by variation in temperature and precipitation variation occurring over semi-arid ecosystems.
Ardö, 2015	Africa	2000–2010	To compare primary production data from remote sensing and dynamic vegetation models.	GPP estimations derived from remote sensing data (i.e. MOD17) are higher than those derived from dynamic vegetation models, while NPP estimations are lower. When validated against ground-based data, both estimations show significant positive correlation.
Liu et al., 2015	China	2000–2011	To assess the WUE of ecosystems and their response to drought	Drought has an impact on WUE, and the response of WUE to drought varies among ecosystem types, geographic locations and climate conditions.
Abdi et al., 2014	Sahel region, Africa	2000–2010	To estimate and analyze the supply and demand of NPP in the Sahel countries.	The demand of NPP increased on an annual rate of 2.2%, but with a near constant supply. The major increase in demand is for food requirement.
Tang et al., 2014	Global	2000–2013	To investigate the WUE of different ecosystems and to study their variation and trends.	WUE varied greatly among ecosystem types and among ecosystems located in different climate zones. Recent changes in land cover led to decline in global WUE.
Zhang et al., 2014	Lower Mekong Basin	2000–2011	To assess the effect of drought on vegetation productivity	Droughts with varied intensities have different impacts on ecosystems, which show variation in response to drought.
Chen et al., 2013	Global	1997–2009	To analyze the impact of drought on NPP	NPP and drought are positively correlated in arid regions, whereas boreal (sub-arctic) areas show negative correlation, and some areas show no correlation.
Zhao and Running, 2010	Global	2000–2009	To detect the trend of NPP and its relation to drought	A global declining trend in the average NPP is detected during the investigation period. The main driving force of this decline is drought.
Zhang et al., 2009	Global	2000–2003	To investigate the pattern of CUE (GPP/NPP) in different ecosystems, geographical locations and climate conditions.	CUE varies considerably based on ecosystem type, geographical location and climate conditions.
Turner et al., 2006	Global	2000–2004	To evaluate the performance of MOD17 products across different biomes and compare it to 9 Eddy covariance flux towers data.	MOD17 products provide good data to detect the general trend of primary productivity, but shows overestimations in low productivity locations and vice versa.

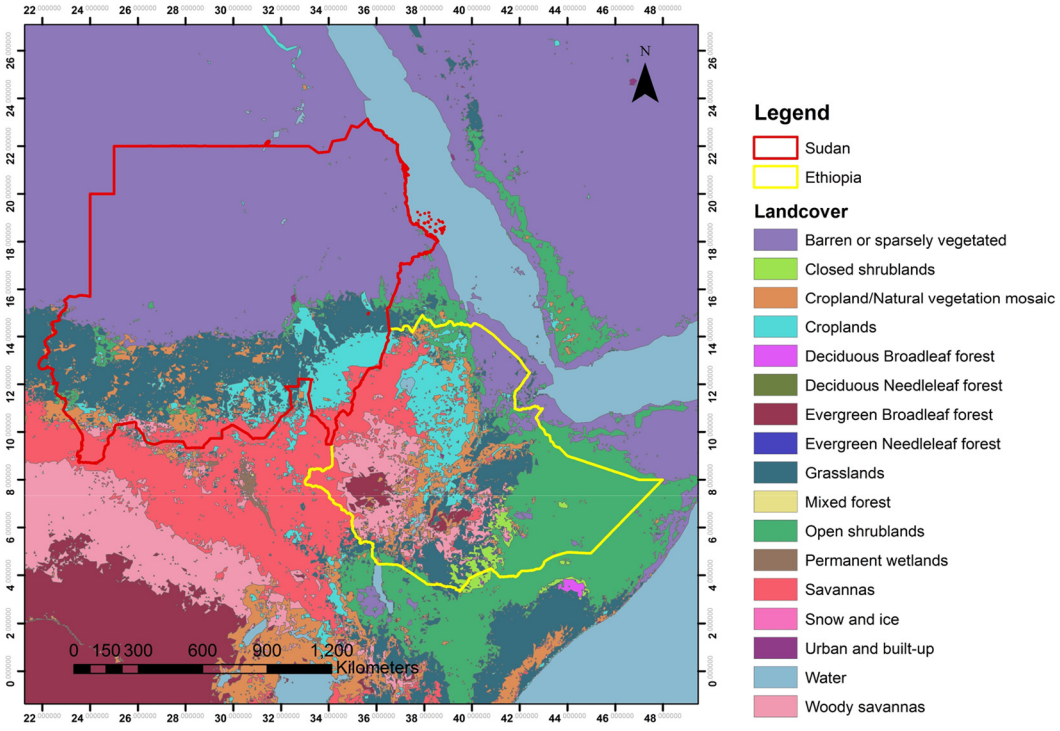

Fig. 1. Location map of East Africa showing the boundaries of the two case studies (Sudan and Ethiopia) and the different land cover types located in the region. Landover data in this map are that of MCD12Q1 product.

change impacts (Abebe, 2014). Moreover, most of the countries in this region are considered among the least developed countries, with a high and rapidly rising population (UNECA, 2016), consequently putting more pressure on the natural resources in the future. With a total area of about 3 million km^2, Sudan and Ethiopia are a good example of land cover types typical for this region (Fig. 1). The two countries together are characterized by a great diversity in land covers, including savannah, permanent wetlands, croplands, shrublands, and forests. Accordingly, they show significant spatial variation in climate conditions, ranging from hyper-arid in northern Sudan to the humid conditions in some parts of the Ethiopian highlands. These features make the two countries particularly suitable for our research. Most of the area in Sudan is bare or sparsely vegetated land (62% of the total area). These areas are mainly located in the northern half of the country (Fig. 2). In Sudan, grassland is the dominant land cover type, covering around 20% of the total area. In Ethiopia, open shrublands represent the largest land cover type, covering approximately 27.6% of the total area. Woody savannah, grasslands and croplands also represent important land covers in Ethiopia in terms of area (Fig. 2).

2.2. Data and methods

Using data acquired from public-domain sources offer a solution for such a data-scarce region. Along with land cover data, time series of the NPP, GPP, Normalized Difference Vegetation Index (NDVI), precipitation, evapotranspiration, temperature and Standardized Precipitation Evapotranspiration Index (SPEI), were used in this analysis (Table 2). All of these data were derived from the public-domain sources for a time frame extending from 2000 through 2013. Most of the remote sensing datasets used in this study are recent products and available only for the years after 2000, for instance, the NPP, GPP and ET_a from MODIS. The selection of the period (2000 − 2013) was mainly controlled by the availability of the data from different sources for the same time period. On the other hand, many studies dealt with the same subjects were conducted for somehow the similar period. We choose the period to be consistent with these researches in order to facilitate the comparison of the findings. Moreover, as mentioned earlier, the period between 2000–2009 was the hottest on the global record; therefore, these years are very interesting for studying the NPP patterns. In this study, the data processing was carried out using ArcGIS 10.3 software.

2.2.1. Primary productivity

Primary productivity data were obtained from MOD17 product (Zhao et al., 2005), which provides NPP and GPP data (in g carbon m^{-2}) from MODIS satellite. MODIS is one of the sensors on NASA's Earth Observing System (EOS) satellites. It provides continuous global monitoring data of primary productivity with a spatial resolution of 1 km and at a temporal resolution of 8-day, monthly and annual intervals. MOD17 version 055 data of annual estimates of NPP and GPP were downloaded from the Numerical Terradynamic Simulation Group website. Invalid values were removed from the raster files; then, each raster file was multiplied by a scale factor of 0.1 to restore the original NPP and GPP values, as instructed in the metadata file of this dataset. Lastly, using "extract by mask" tool in ArcGIS, separate raster time series of NPP and GPP were produced for each of the two countries, i.e. Sudan and Ethiopia.

With limited available ground data in comparison with MOD17 data, validation of MODIS data is a challenge (Zhao et al., 2005). Numerous studies were conducted to compare the MOD17 data with field measurements. A detailed overview of the performance of this product is beyond the purpose of this research. Nevertheless, it is worth mentioning for instance that Turner et al. (2006) used Eddy flux towers to validate MOD17 data and found that MOD17 datasets show no overall bias when compared with towers data. They found, however, that MOD17 data tend to overestimate primary productivity in the low productivity areas and underestimate it in high productivity areas. Zhao et al. (2005) made many enhancements in the main inputs of this dataset and reported on correlation analyses between MOD17 and ground-based data. Ardö (2015) compared MOD17 NPP with Aboveground NPP (ANPP) data collected from ground measurements in 35 sites in Sudan. While they found a strong correlation between the multi-year average MOD17 NPP and the ANPP ($r = 0.80$, RMSE = 135 g), they also reported a systematic over-estimation of MOD17 NPP, which is attributed to the fact that the ANPP only considers aboveground biomass.

2.2.2. Normalized Difference Vegetation Index (NDVI)

Data on the NDVI were obtained from the website of the Famine Early Warning Systems Networks (FEWS NET). This dataset was developed by the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center. The data used herein were 10-day composite data with a spatial resolution of 250 m. The raw NDVI images processing involved: (i) eliminating the invalid values, (ii) converting the digital numbers (DN) provided in the raster files to NDVI values, using the formula NDVI = (DN − 100) / 100, as per instruction of the product documentation; (iii) using "extract by mask" tool to create separate NDVI data for each country from the original tiles of East Africa; (iv) aggregating 10-day composite data into monthly time steps, using maximum value composite (MVC) method (Holben, 1986), which selects

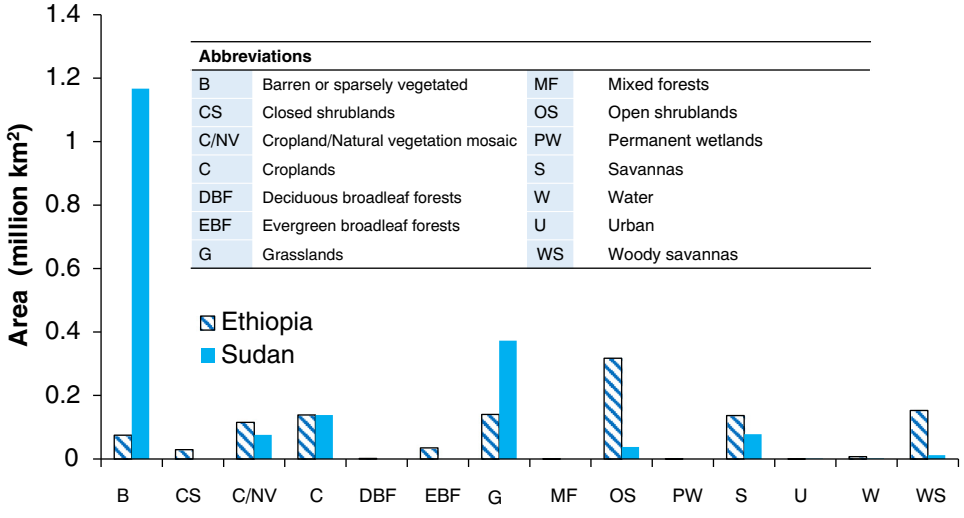

Fig. 2. Total area of each land cover in Sudan and Ethiopia as appear in the MDC12Q1 product.

Table 2
Specification of the data used in this study.

Dataset	Source	Reference	Temporal resolution	Spatial resolution	Download site	Performance
Net Primary Productivity (NPP)	MOD17	Zhao et al. (2005)	Annual	1 km	http://www.ntsg.umt.edu	Data differ from field measurements by 28%
Gross Primary Productivity (GPP)	MOD17	Zhao et al. (2005)	Monthly	1 km	http://www.ntsg.umt.edu	
Precipitation (P)	CHIRPS	Funk et al. (2015)	10-day composite	5 km	http://earlywarning.usgs.gov/fews/datadownloads/Global/CHIRPS%202.0	CHIRPS correlations with gridded ground precipitation data is with R > 0.75 in many areas of the world
Actual Evapotranspi-ration (ET_a)	MOD16	Mu et al. (2007); Mu et al. (2011)	Monthly	1 km	http://www.ntsg.umt.edu/project/mod16	Correlation coefficient between MOD16 and tower data is 0.86 (Mu et al., 2011)
Normalized Difference Vegetation Index (NDVI)	e-MODIS NDVI, Famine Early Warning Systems Network (FEWS NET)	–	10-day composite	0.25 km	http://earlywarning.usgs.gov/fews/datadownloads/East%20Africa/eMODIS%20NDVI	
Temperature (T)	University of Delaware (UDel)	Willmott and Matsuura, 2001	Monthly	50 km	http://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html#detail	
Drought index	Standardized Precipitation Evapotranspiration Index (SPEI)		Monthly	50 km	http://www.sac.csic.es/spei	
Land cover	MCD12Q1	–	–	0.5 km	https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12q1	

the maximum value for each pixel from the three 10-day composite images. Integrated NDVI (INDVI) for the cultivation season was used as a proxy for accumulated biomass (Field et al., 1995; Prince and Goward, 1995). It was calculated as a summation of the NDVI for June – October, which represents the main growing season in the region (Elagib, 2014, 2015).

2.2.3. Precipitation

In the current study, we used Climate Hazards Group InfraRed Precipitation with Station data, CHIRPS (Funk et al., 2015) version 2.0 with a spatial resolution of 0.05°. Processing of precipitation data for this research included aggregation of the original 10-day composite data into monthly and annual data. Then, extract-by-mask tool in GIS was used to produce time series of precipitation for Sudan and Ethiopia. CHIRPS product is a gridded precipitation dataset, which is developed by the United States Geological Survey (USGS) to provide high-quality precipitation data to be used for early warning missions and drought monitoring. Blending remote sensing estimations with in-situ data from climate stations, including stations in Sudan and Ethiopia, results in a good reliability of this dataset (Funk et al., 2015).

2.2.4. Temperature

A temperature product developed by the University of Delaware (UDel) was used in this investigation. UDel provides gridded monthly air temperature data with a spatial resolution of 0.5° for the whole globe (Willmott and Matsuura, 2001). This dataset covers the period from 1901 to 2014. Data of UDel product uses observations at ground weather stations. The last version (V4.01) of this dataset was used herein. As with the pervious datasets, monthly temperature data were also processed and time series rasters were produced for each country over the study time period and later aggregated to annual averages.

2.2.5. Actual evapotranspiration (ET_a)

Only few public-domain sources provide data on actual evapotranspiration (ET_a). For the purpose of this study, MOD16A2 product was used. MOD16A2 is a monthly ET_a datasets offered by a NASA/EOS project. It provides global evapotranspiration data using input data from MODIS satellite. The data come in a 1 km spatial resolution and at 8-day, monthly and annual temporal resolution. This product uses an ET algorithm developed by Mu et al. (2007) and improved by Mu et al. (2011) to calculate ET_a based on the Penman-Monteith equation (Monteith, 1965).

MOD16 provides a special product for the Nile basin which is the one used herein. This product overcomes the problem encountered by the regular MOD16A2 datasets of not considering deserts, which is one of the major ecosystems in the region. Processing of MOD16A2 raw data considered excluding invalid values by removing the pixels of these values and restoring the original ET_a values form the DN. Separate raster time series were created for Sudan and Ethiopia.

This product was validated using ground data by several researchers. Some researchers found inconsistency between MOD16 ET and ground data. For instance, Ramoelo et al. (2014) used ET_a data for savannah and woodland ecosystems between two eddy covariance flux towers in South Africa and MOD16 ET_a. Their analysis showed that due to parameterization of the Penman-Monteith model and flux tower measurement errors, MOD16 underestimates ET_a by 2–7 mm per 8 days. In contrast, Tang et al. (2015) found a good agreement between MOD16 ET_a and eddy covariance and large aperture scintillometer measurements in north and northwest China. Validation studies of this product over East Africa are few. Al Zayed et al. (2016) have validated MODIS ET_a (MOD16A2) among other satellite-based ET_a estimation methods using field-scale water balance over the Gezira Irrigation Scheme in central Sudan. They found that, on a regional scale, MOD16A2 is one of the more useful operational products, yet, MOD16 algorithm tended to overestimate (underestimate) low (high) ET_a values. Despite the observed differences between the ground measurements and MOD16

product, this product provides essential knowledge on the water cycle and its interaction with environmental changes (Mu et al., 2007). It provides easily accessible information for areas with limited surface data like the region of Sub-Saharan Africa.

2.2.6. Drought index data

Because drought is a slow phenomenon that develops over a long time without precipitation (Gillette, 1950; Wilhite and Glantz, 1985), drought indices that take different timescales into account are very useful for drought assessment. Incorporating different time scales in the assessment of drought impact is widely used (Potopová et al., 2015). In the current investigation, we used the Standardized Precipitation Evapotranspiration Index (SPEI) - developed by Vicente-Serrano et al. (2010) - with a spatial resolution of 0.5° and a monthly time step. SPEI calculation requires precipitation and temperature data to account for the difference between precipitation and potential evapotranspiration (PET), i.e. a simple water balance. SPEI is a multi-scalar index that allows comparison of drought severity over different time scales and across space. For the SPEI scale ranges refer to Table 3. As SPEI is a standardized variable, it can be compared with other SPEI values over time and space. The most widely used time steps are 1, 3, 6, 12 and 24 months, denoted by SPEI01, SPEI03, SPEI06, SPEI12 and SPEI24, respectively (Chen et al., 2013). In the current investigation, we used SPEI01, SPEI03, SPEI06 and SPEI12.

2.2.7. Land cover

In the current research, MCD12Q1 land cover dataset (Friedl et al., 2010) provided by the Land Processes Distributed Active Archive Center (LP DAAC) was used. This product provides annual land cover data for the whole globe with a spatial resolution of 1 km for the period spanning 2001 to 2012. The latest land cover data (version 051) was used herein, with land cover classification scheme of the International Geosphere-Biosphere Programme (IGBP). The global land cover layer was processed to generate separate layers of land cover classes for each country.

2.2.8. Correlation of the variables and calculation of water and carbon uses efficiency

The NPP and climate elements were further standardized according to Kraus (1977) to analyze the inter-annual variability of the Standardized Anomaly Indices (SAIs). Before standardization, the data for all variables were tested for normality using the Shapiro-Wilk test (Shapiro and Wilk, 1965; Ghasemi and Zahediasl, 2012). Employing an online calculator (Dittami, 2009), the data were found to be normally distributed. For each variable, the SAI was calculated as: {value − average (2000–2013)} / standard deviation (2000–2013). The annual average of each climate variable for each land cover class was calculated using the functions of the GIS environment. Fig. 3 shows the procedure followed in this study to correlate the variation in the annual NPP and climate indices. This procedure was used for all land cover classes and for each year using the non-parametric Spearman's coefficients (ρ, rho), with the aid of XLSTAT V.19.4 software (Addinsoft, 2017). Croplands and grasslands were considered in the analysis of the impact of climate variability on food production on a monthly time step for two selected years (2007 and 2009) representing a wet and a dry year, respectively (Sulieman and Elagib, 2012; Elagib, 2013). For the two years, 10-day composite NDVI data were summed for the five cultivation months (June–October), and the seasonal INDVI was used as a proxy of vegetation productivity as explained before. Annual average WUE and CUE were calculated for each land cover type as the ratios of NPP to ET_a and NPP to GPP, respectively. SAIs of WUE and CUE were also calculated for the purpose of investigating the linkage between them and SAIs of the climate elements.

Table 3
Categories of the SPEI scale.

Class	SPEI value
Extremely wet	≥2.00
Severely wet	1.5 to 1.99
Moderately wet	1.00 to 1.49
Normal	0.99 to −0.99
Moderately drought	−1.00 to −1.49
Severe drought	−1.50 to −1.99
Extreme drought	≤−2.00

3. Results & discussion

3.1. Climate conditions during 2000–2013

In general, precipitation in Sudan is much less than in Ethiopia. Temporally, precipitation shows some variation from year to year in both countries (Fig. 4a). The year with the lowest precipitation in Sudan was 2004, recording 180.3 mm. For the period 2000–2013, the areal average total annual precipitation is 227.9 mm and the coefficient of variation (CV) is 0.13 for Sudan. As for Ethiopia the corresponding values are 808.8 mm and 0.08 (Fig. 4a). The results on average precipitation obtained from CHRIPS are comparable with the 1970–2000 averages (i.e. 225.5 mm and 799.1 mm for Sudan and Ethiopia, respectively, as estimated using WorldClim (Fick and Hijmans, 2017)). Mostly vegetated lands in Sudan are found on an east-west belt located in the southern part of the country whereas characterized by precipitation amounts between 250 and rarely above 1000 mm. Large areas of the northern part of Sudan receive <250 mm per year. As for Ethiopia, the annual precipitation is on average >2000 mm, with the highest precipitation occurring in the western part whereas the lowest precipitation is recorded in the northeastern and southeastern portions of the country.

In the study area, it is essential to understand the timing of precipitation as a crucial factor in the vegetation development. Sudan and Ethiopia are relying mostly on rainfed agriculture for domestic food production. The rainy season and growing season are almost identical, and they extend from June to October. In Sudan, even the timing of the main growing season for irrigated agriculture synchronizes the rainy season, especially in the large irrigated schemes (e.g. Gezira and Rahad) because the water supply in these schemes is highly dependent on the River Nile flow which is in turn highly variable due to the seasonal variability in precipitation.

On the average, most of Sudan shows annual ET_a of <500 mm. The southern part displays ET_a up to 1500 mm. Some of the irrigated agricultural schemes (e.g. Gezira) in central Sudan show an average ET_a between 500 mm and 1000 mm. The country's annual average of ET_a is 204.4 in Sudan and 530.2 mm in Ethiopia (Fig. 4b). Spatial variation in ET_a takes the same pattern as that of precipitation. The highest ET_a values are for water bodies, e.g. Lake Tana in Ethiopia (Fig. 4b).

The 14-year annual average temperature is 28.1 °C in Sudan and 23.1 °C in Ethiopia. During the study period, the highest average annual temperature detected for each country was 29.0 °C in Sudan in 2010 and 23.5 °C in Ethiopia in 2009. Regionally, the center of Sudan is the area characterized by the highest temperature (Fig. 4c).

On a monthly time scale, the most severe droughts in the region during the study period occurred in 2004, 2005 and 2009 (Fig. S1). During these years, Sudan was affected by moderate to severe drought while moderate drought conditions prevailed during only few months in these years in Ethiopia. Based on the annual data (Fig. 5a and b), Sudan was affected by a moderate drought in 2009 whereas the rest of the years were normal. Ethiopia experienced normal moisture conditions during the same period.

3.2. Net Primary Productivity during 2000–2013

Spatially, the highest NPP values in Sudan are found along the southeastern and southwestern borders of the country where most of the savannah are located (Fig. 6a). The majority of the northern parts of the

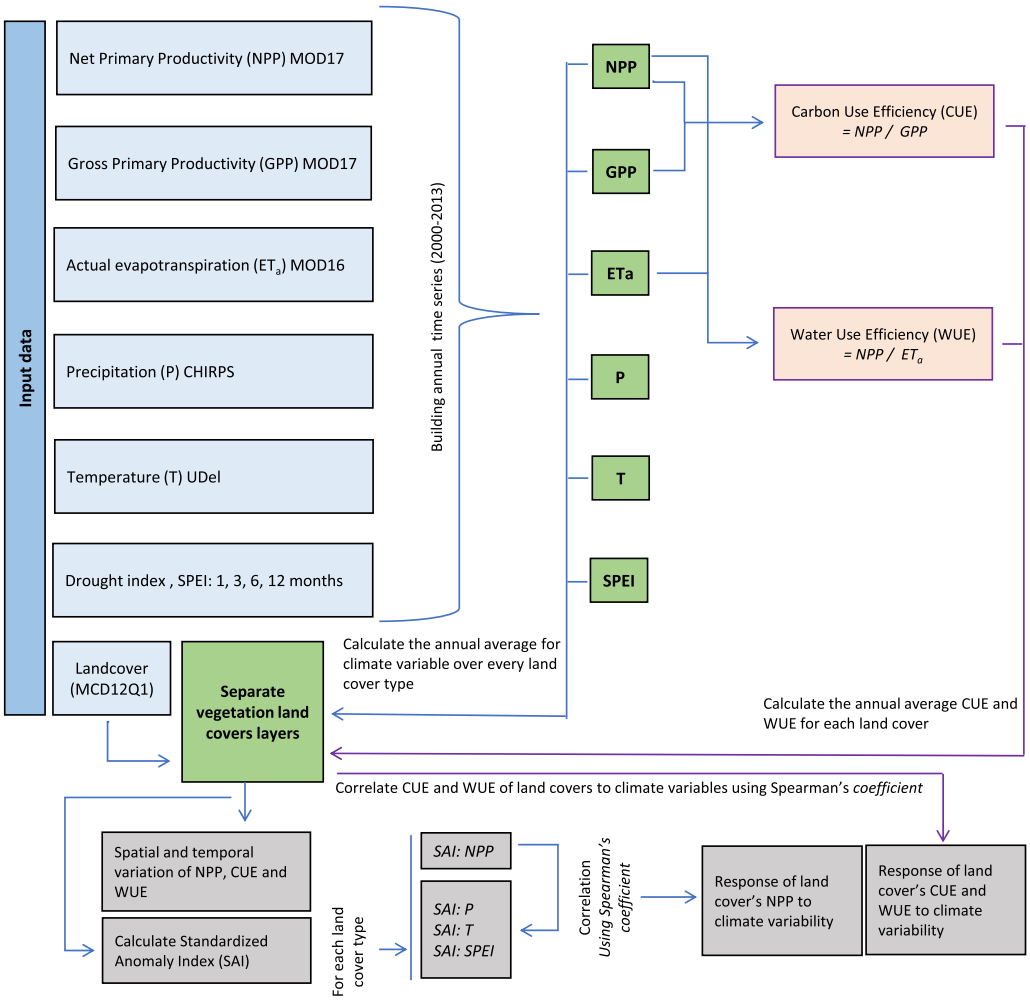
Input data
Net Primary Productivity (NPP) MOD17
Gross Primary Productivity (GPP) MOD17
Actual evapotranspiration (ETa) MOD16
Precipitation (P) CHIRPS
Temperature (T) UDel
Drought index , SPEI: 1, 3, 6, 12 months
Building annual time series (2000-2013)
NPP
GPP
ETa
P
T
SPEI
Carbon Use Efficiency (CUE) = NPP / GPP
Water Use Efficiency (WUE) = NPP / ETa
Landcover (MCD12Q1)
Separate vegetation land covers layers
Calculate the annual average for climate variable over every land cover type
Calculate the annual average CUE and WUE for each land cover
Correlate CUE and WUE of land covers to climate variables using Spearman's coefficient
Spatial and temporal variation of NPP, CUE and WUE
Calculate Standardized Anomaly Index (SAI)
For each land cover type
SAI: NPP
SAI: P
SAI: T
SAI: SPEI
Correlation Using Spearman's coefficient
Response of land cover's NPP to climate variability
Response of land cover's CUE and WUE to climate variability

Fig. 3. Flowchart of the methodological procedure followed in this study to correlate the inter-annual variability in NPP, CUE and WUE and their response to climate variability and drought conditions.

country are barren areas with too low NPP rates compared to the vegetated areas within the country. In Ethiopia, the highest NPP values characterize the middle part of the country that is covered mostly by woody savannah and evergreen broadleaf forests (Fig. 6b). The areas with the lowest NPP rates are located in the northeastern part of the country which is mostly barren, sparsely vegetated or covered by open shrublands. The annual average NPP is 87.24 and 501.92 g carbon for Sudan and Ethiopia, respectively. All of the land covers in Ethiopia show higher NPP than their correspondents in Sudan. This could be attributed to the higher precipitation and larger vegetated lands in Ethiopia compared to Sudan. On average, evergreen broadleaf forests and woody savannah in Ethiopia show the highest annual NPP, with NPP values of 1279.5 and 845.3 g Carbon/m^2, respectively.

3.3. Variation of primary productivity and correlation with climate variability

Throughout the period from 2000 to 2013, the NPP displayed high inter-annual variability in both countries. In Sudan, most of the land cover types showed negative anomalies during the years 2000–2008 (Fig. 7a). The year 2007 was an exception, probably because it was a year with a relatively high precipitation. The last five years (2009–2013) witnessed an increase in NPP of all land cover types. NPP for the year 2002 was associated with the largest drop for all land covers. Drought effect in two successive years (2001 and 2002) is likely to be the reason behind this considerable drop in NPP. In comparison with Sudan, some land covers in Ethiopia displayed positive NPP anomalies during the first years of the study period, mainly due to the high precipitation. The impact of drought of 2002 in some land cover types (e.g. closed shrublands, croplands mixed forest and savannah) was notable as NPP in these land covers showed negative anomalies.

As mentioned earlier, many drivers regulate the inter-annual variability of NPP. In arid and semi-arid areas, such as the study area, patterns of precipitation and temperature are likely to be the most important climatic factors, but the interactions of these climatic factors with vegetation activities are complex (Li et al., 2016). From the analysis, it can be noted for Ethiopia that the variability in NPP is influenced directly by the variability in precipitation (Fig. 7). This is manifest by the in-phase response of NPP to changes in precipitation and by Spearman's ρ (Fig. S2). Among all land cover types in Ethiopia, grasslands revealed the strongest correlation ρ value ($\rho = 0.82$, $p = 0.05$). The correlation with closed shrublands, croplands, deciduous broadleaf forests, grasslands and permanent wetlands were significant whereas the correlation for evergreen broadleaf forests, mixed forests, open shrublands, savannah and woody savannah were statistically insignificant. In Sudan, the correlation was statistically insignificant at $p = 0.05$ (Fig. S3). Zhang et al. (2014) listed many biotic and abiotic factors (e.g. soil properties, nutrient, availability and temperature) to be responsible for the lack of immediate response of NPP to the current-year precipitation. Spatially, the highest correlation between NPP and

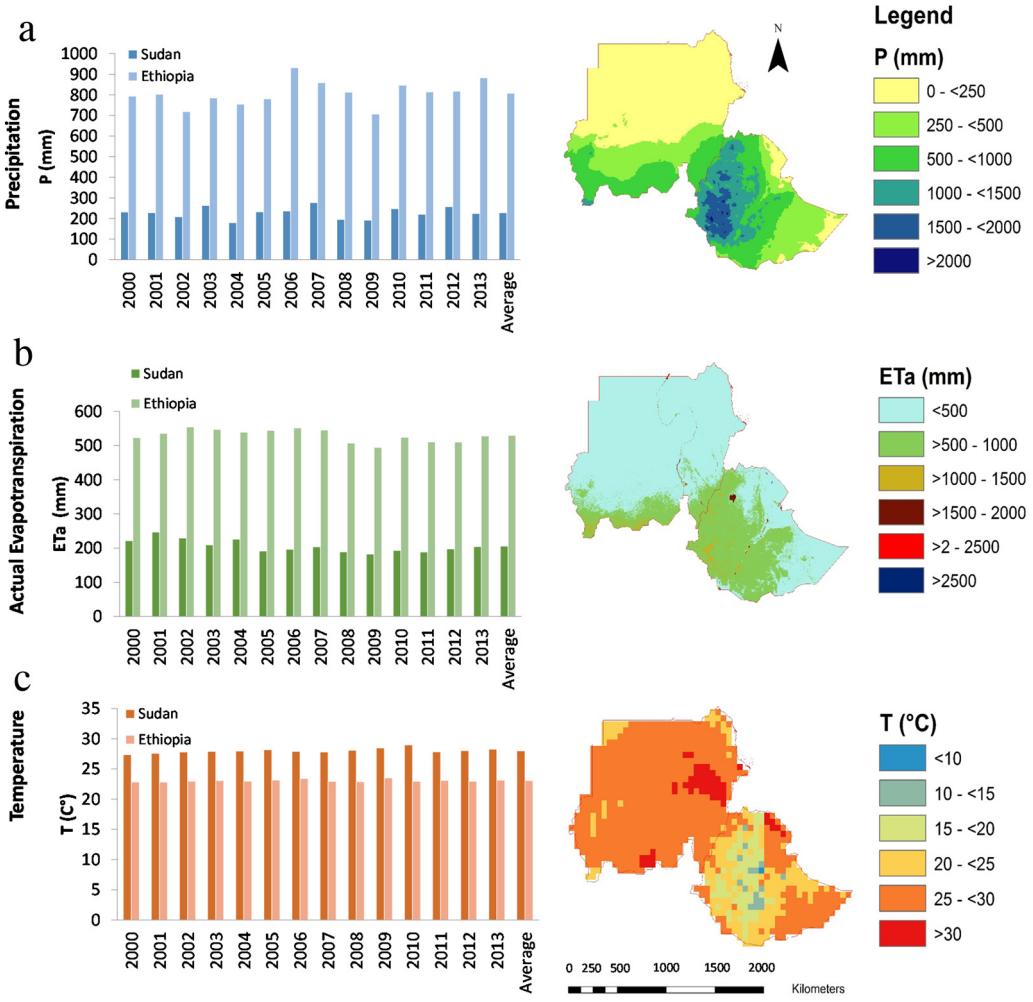

Fig. 4. Temporal and spatial variation in climate elements inSudan and Ethiopia: (a) precipitation, (b) actual evapotranspiration and (c) temperature.

precipitation is detected in the eastern and southern Ethiopia (Fig. 8). The Spearman's ρ in these areas is >0.6. These areas are dominated by croplands, grasslands and savannah. Only small spots in the central (Gedaref and Blue Nile states) and western parts of Sudan exhibited ρ values >0.6. The former is characterized by extensive croplands (both irrigated and rainfed agriculture). However, the correlation between NPP and precipitation in these areas were statistically insignificant. Statistical analysis showed no significant correlation between the inter-annual variation in mean annual temperature and NPP for all land covers in both countries. Several land cover types showed insignificant correlation between the inter-annual variation in temperature and NPP (Fig. 8). Lack of correlation between inter-annual variabilities in temperature and NPP in arid and semi-arid regions were detected in some parts of the world, as reported by Liang et al. (2015) for China. These findings may suggest that the land cover types in Ethiopia are more sensitive to variation in precipitation than those characterizing Sudan. However, since this analysis was conducted on only an annual basis, further analysis on the varying seasonal effects on vegetation development is deemed imperative to draw a more solid conclusion.

3.4. Drought impact on primary productivity

Drought affects the annual NPP in the land covers of Sudan and Ethiopia differently. While all land cover types in Ethiopia show a positive significant correlation ($p = 0.05$) between NPP and drought severity, no statistically significant correlation was detected for Sudan. Lack of correlation between annual NPP and the SPEI was also found by Peng et al. (2017) for many countries (e.g. Indonesia, Philippines and Malaysia). By correlating SPEI at different time scales (1, 3, 6, and 12 months) with NPP anomalies, we found the highest correlation with the annual NPP anomalies for SPEI03 in Ethiopia. Thus, drought events on a time scale of 3 months largely control NPP in this country. This high dependence can be detected spatially. Large areas in Ethiopia showed statistically significant correlation between NPP and SPEI03 compared to drought indices at other time steps (Fig. 8). Savannah also showed a very strong positive correlation between NPP anomalies and SPEI at a time step of three months ($\rho = 0.93$, $p = 0.05$). Open shrublands in Ethiopia seem to be more sensitive to drought as their NPP showed strong positive correlation with a drought of one month (SPEI01) ($\rho = 0.84$, $p = 0.05$). The NPP for croplands and permanent wetlands displayed the weakest relationship with SPEI03 ($\rho = 0.66$ and 0.63 respectively, $p = 0.05$). This relatively lower correlation suggests that these two land covers are less sensitive to drought than the other land covers due to agricultural management (e.g. irrigation) and/or sufficient water supply from tributaries or groundwater. Evergreen broadleaf forests seem to be quite resistant to drought since their inter-annual NPP anomalies showed a moderate correlation with SPEI ($\rho = 0.54$ with SPEI01, $p = 0.05$). Deeper rooting (Song et al., 2017) and access to larger water stores in soils and groundwater could be a reason. All of the land cover types in Sudan showed no statistically significant correlation between their annual NPP anomalies and SPEI at any of the time scales.

The total NPP in the dry year 2009 increased by 20.1% in Sudan and decreased in Ethiopia by 11.4% from the 14-year country's average

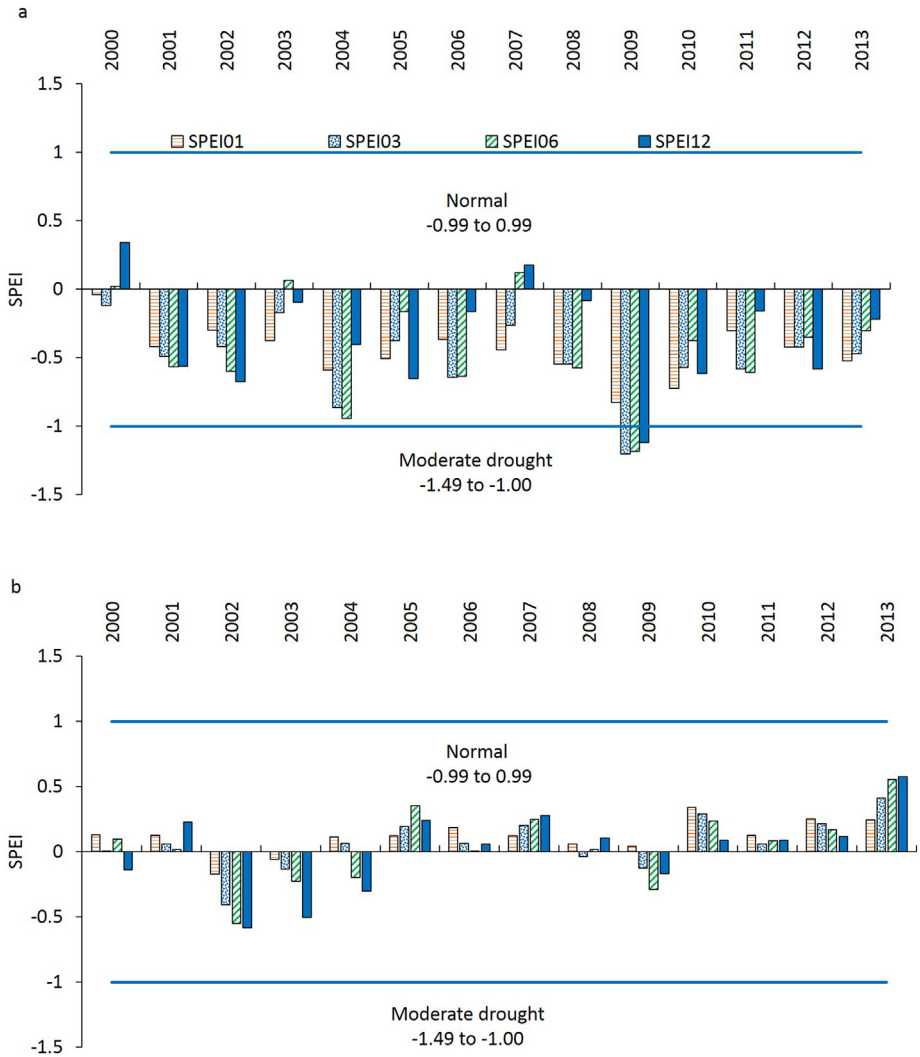

Fig. 5. Time series of SPEI for in the study area with different time steps 1, 3, 6 and 12 months, (a) Sudan and (b) Ethiopia.

(2000–2013). The increase of NPP in dry years is reported for many areas around the world, for example in Northeast China (Liu et al., 2015; Sun et al., 2016; Pei et al., 2013). Generally, there are three potential causes of this phenomenon as reported by Yang et al. (2016), Liu et al. (2015) and Pei et al. (2013). These causes are (i) the association of increase in temperature with drought conditions, (ii) the memory effect of the previous year drought on the current year NPP and (iii) the characteristics of drought. In the case of the dry year 2009 in Sudan, all these factors seem to have played a role in increasing the NPP. It can be explained partly by the notable increase in the annual temperature in this year (Fig. 7), which was the hottest on the record as reported by Sulieman and Elagib (2012) for eastern Sudan. Temperature plays a key role in the plant respiration process, thus contributing to increasing NPP (Zhao and Running, 2010). In particular, mild drought when coupled with high temperature, it might offset the decrease of NPP induced by water deficit, i.e. leading to an increase in the NPP (Sun et al. 2016; Liu et al. 2015). In contrast, temperature during the dry year of 2004 was below the multi-year average which might have contributed to the decrease in the annual NPP. Additionally, the memory effect of drought also impacts the NPP (Yang et al., 2016), likely decreasing the NPP in the dry year of 2002 due to cumulative drought of the years 2001 and 2002. Contrary to this, the relatively milder drought condition in 2008 probably weakened the drought impact of 2009 on NPP. The timing of drought during the year, especially the beginning of the growing season, is also an important factor determining the levels of crop yield (Bussmann et al. 2016; Elagib, 2015; Elagib, 2013) and NPP. In Northeast China, autumn drought was found to lead to larger reduction in NPP whereas spring drought had insignificant impact (Liu et al., 2015). Frolking (1997) found that late summer drought increased NPP by about 20% due to reduced respiration. The present analysis of drought characteristics in Sudan shows a stronger intensity but lesser spatial extent of drought in 2009 compared to a stronger drought in other dry years (e.g. 2002) during the beginning of the season (e.g. July). These drought characteristics resulted in a relatively higher NPP in many land covers (e.g. croplands and shrublands) in July in 2009 which is less by 33% from the NPP of the same month in the wet year, 2007.

3.5. Intra-annual variability of primary productivity and drought

Results of monthly GPP and NDVI for croplands and grasslands showed the same temporal patterns in 2007 and 2009. GPP and NDVI start to increase remarkably at the beginning of the rainy season (i.e. June) as shown in Fig. 9. The average NDVI showed lower values during the drought year 2009 in both countries and for both types of land covers. A strong correlation was found between the monthly NDVI and monthly GPP for the two land covers in both countries (Fig. S4). The drought condition of 2009 reduced both the monthly NDVI and GPP during the rainy months. The reduction in the NDVI was more noticeable in Sudan compared to Ethiopia. Accordingly, the decline in

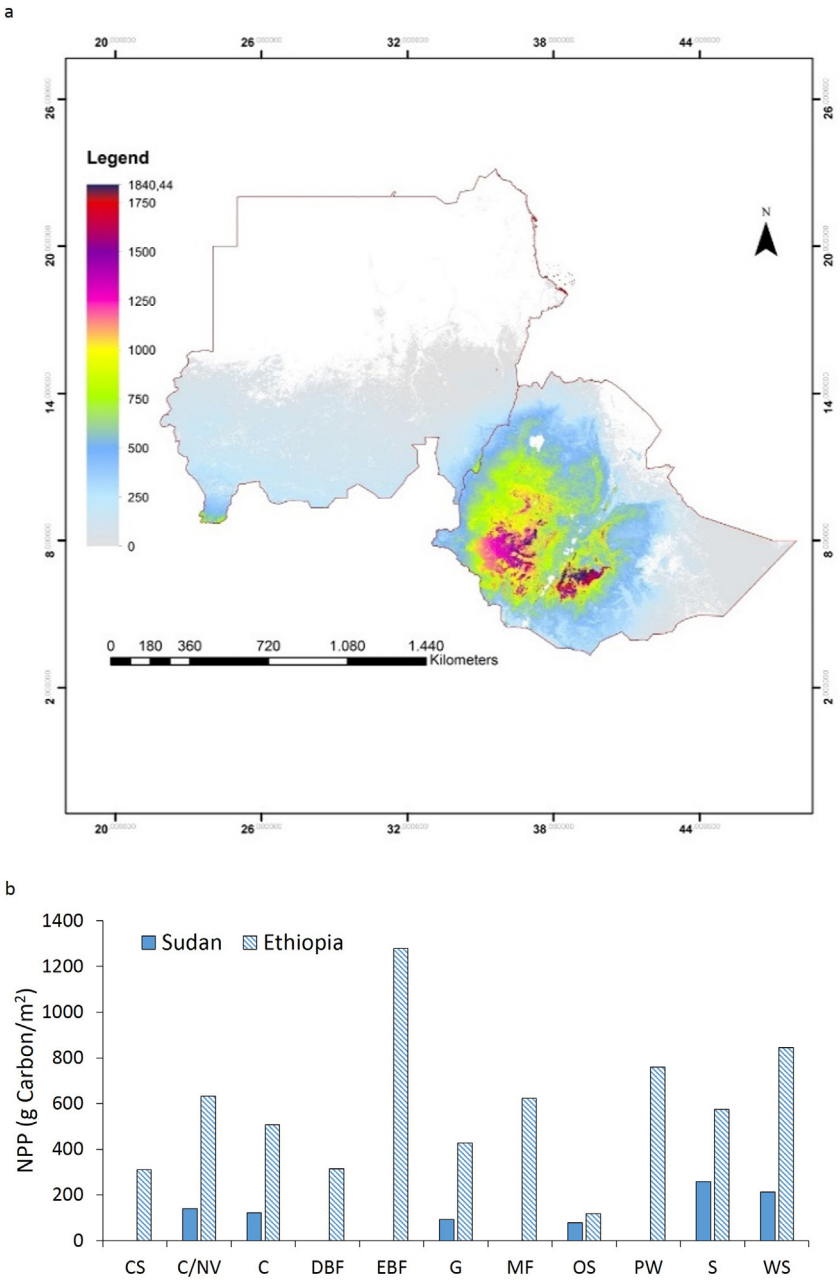

Fig. 6. (a) Spatial variation of the average NPP in Sudan and Ethiopia as modeled by MOD17. (b) Multiyear annual average (2000–2013) of NPP for land cover types in Sudan and Ethiopia.

iNDVI for croplands and grasslands in 2009 compared to 2007 were 16.9 and 14.9% in Sudan and 7.1 and 16.1% in Ethiopia, respectively. Statistical correlation between the intra-annual variations in GPP and intra-annual variations in precipitation, temperature and SPEI revealed weak correlation for croplands and shrublands in both countries. The highest correlation between GPP and SPEI03 was detected for Sudan with Spearman's ρ of 0.58 and 0.59 for croplands and shrublands, respectively.

3.6. Water use efficiency (WUE)

The magnitude of WUE varies depending on the magnitudes of NPP and evapotranspiration. The national multiyear average WUE for Sudan is lower (0.24 g C kg^{-1} H_2O) as compared to that for Ethiopia (0.74 g C kg^{-1} H_2O) due to lower NPP and higher evapotranspiration for the former. Literature shows comparable values for the Ethiopian average WUE and the national average WUEs for China (0.79 g C kg^{-1} H_2O) as reported by Liu et al. (2015), and for the southern United States (0.71 g C kg^{-1} H_2O) as indicated by Tian et al. (2010), but higher values for the global average (0.92 g C kg^{-1} H_2O), as reported by Ito and Inatomi (2012).

Variations are noticeable for the same land cover types under different climate conditions in Sudan and Ethiopia. Evidence of large variations in WUE were also presented by other researchers for different land cover types due to differences in carbon uptake and water consumption (Liu et al., 2015). This dissimilarity is mainly due to physiological differences and climate conditions (Tang et al., 2014). Generally, all of the land cover types in Ethiopia show higher WUE than their counterparts in Sudan (Fig. 10). For instance, the savannah shows an average WUE of 0.31 g C kg^{-1} H_2O in Sudan but 0.75 g C kg^{-1} H_2O in Ethiopia. In Ethiopia, the evergreen forests have higher WUE than the deciduous forests. These figures are in agreement with results reported for forests in similar latitudes (Tang et al., 2014). Among all the land cover types in the region, evergreen broadleaf forests and woody savannah exhibit the

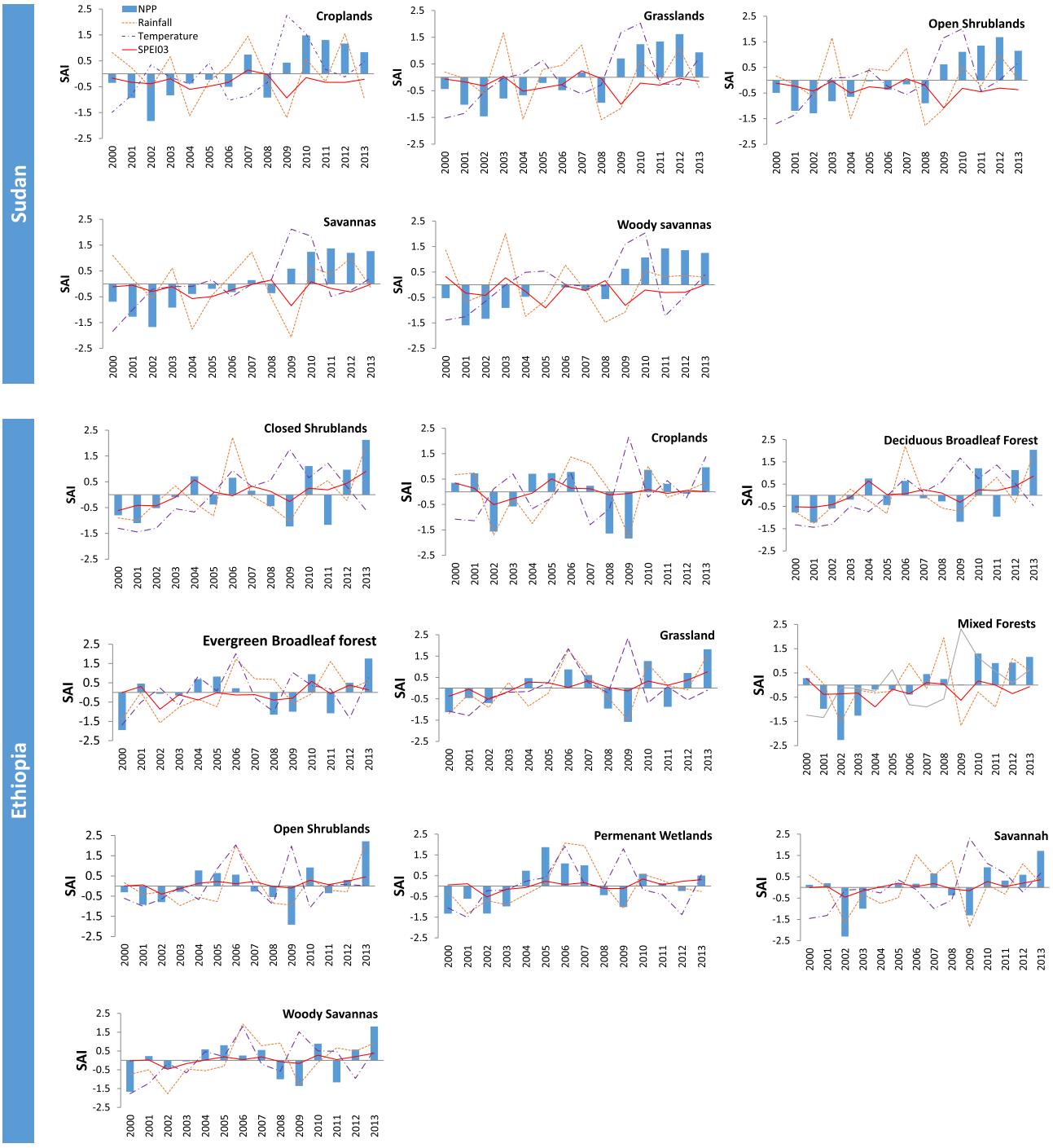

Fig. 7. Inter-annual anomalies of NPP and climate elements (precipitation, temperature and drought (SPEI)) for different land covers in Sudan and Ethiopia.

highest average WUE. They displayed a WUE of 1.4 and 1.07 g C kg^{-1} H_2O, respectively.

In Sudan, the highest WUE is that of Savannah, which shows an average value of 0.31 g C kg^{-1} H_2O. WUE of open shrublands, grasslands, and croplands are 0.278, 0.274 and 0.236 g C kg^{-1} H_2O, respectively. WUE shows great inter-annual variation in the region during the study period. The data for Sudan show a positive anomaly during the period 2009–2013. This increase is detectable for all land cover types and is due to an increase in NPP and a decrease in evapotranspiration. When the inter-annual variations in WUE and SPEI were correlated, the land cover types in Sudan exhibited no significant correlation (Fig. S5). Most of the land covers in Ethiopia show the strongest correlation between annual NPP and SPEI01 and SPEI03 (Fig. S6). This might reflect a high degree of sensitivity of the land covers found in Ethiopia to drought compared to those found in Sudan. Negative correlation between variations in WUE and drought is typical for arid areas (Huang et al., 2017).

In the current study, the 2009 drought induced an increase in WUE in most land cover types in Sudan. The highest increase in this year is detected in woody savannah with a percentage up to 42.2% of the multi-year average WUE in Sudan. An increase in precipitation in arid and semi-arid areas may induce a larger increase in NPP than in evapotranspiration (Liu et al., 2015). Though the response of WUE to drought is not so clear (Liu et al., 2015), many studies (e.g. Dong et al., 2011;

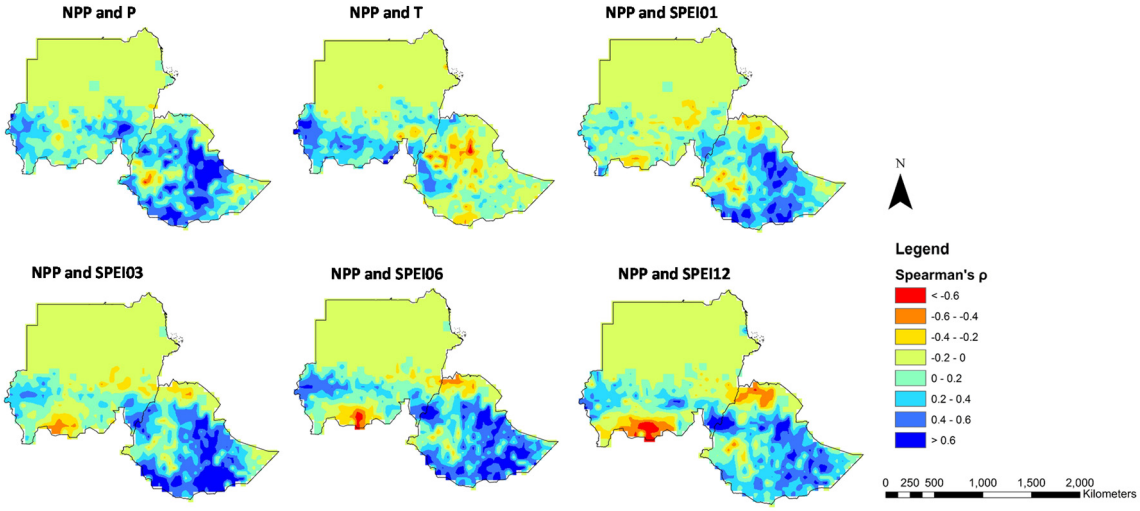

Fig. 8. Spatial pattern of correlation between the anomalies of NPP and both the anomalies of climate elements and drought indices for the period 2000–2013.

Reichstein et al., 2002; Tian et al., 2011) reported an increase in WUE due to drought. The increase in WUE under drought results mainly from internal mechanisms of stomata which work to reduce water losses as a measure of adaptation to water stress (Reichstein et al., 2002). Also, a decrease in frequency and duration of precipitation may result in a reduction of the evaporative fraction of evapotranspiration in favour of transpiration, thus indicating a shift of available water from plant towards deeper soil moisture or groundwater resources. In contrast, all land cover types in Ethiopia showed a decrease in WUE in the same year. The largest decrease (13.3%) was in permanent wetlands when compared to the multi-year average WUE. These observations suggest different responses of WUE for different biomes and different climate conditions.

3.7. Carbon use efficiency (CUE)

In comparison with CUE for Sudan, CUE for Ethiopia shows less inter-annual variability for most land covers. This could be attributed mainly to the high precipitation in Ethiopia since CUE usually shows a constant value where precipitation is high (Zhang et al., 2009), indicating that CUE in these regions is not regulated by water availability. Accordingly, statistical analysis showed insignificant correlation between the variations in CUE and precipitation for most land covers. In contrast to Ethiopia, in Sudan both WUE and CUE increased during the years 2009–2013. The lowest CUE was found in 2005 and 2006 (Fig. 11) as dry years exhibit high respiration (Metcalfe et al., 2010) and low NPP.

All land cover types in Sudan display much lower CUE values than their counterparts in Ethiopia (Fig. 11), mostly due to higher temperature leading to higher respiration (Shaver et al., 2000) in Sudan. In turn, this suggests a larger release of CO_2 from the land cover types in Sudan, or in other words, land cover types in Ethiopia sequester more CO_2. Generally, more CO_2 is released through respiration where the climate is dry and warm whereas CO_2 uptake is the dominant flux in cool and moist climates (Ahlström et al., 2015). CUE exhibits great variation among the vegetation land cover types. Croplands in Ethiopia show the highest annual average CUE (0.59) among all land cover types in the

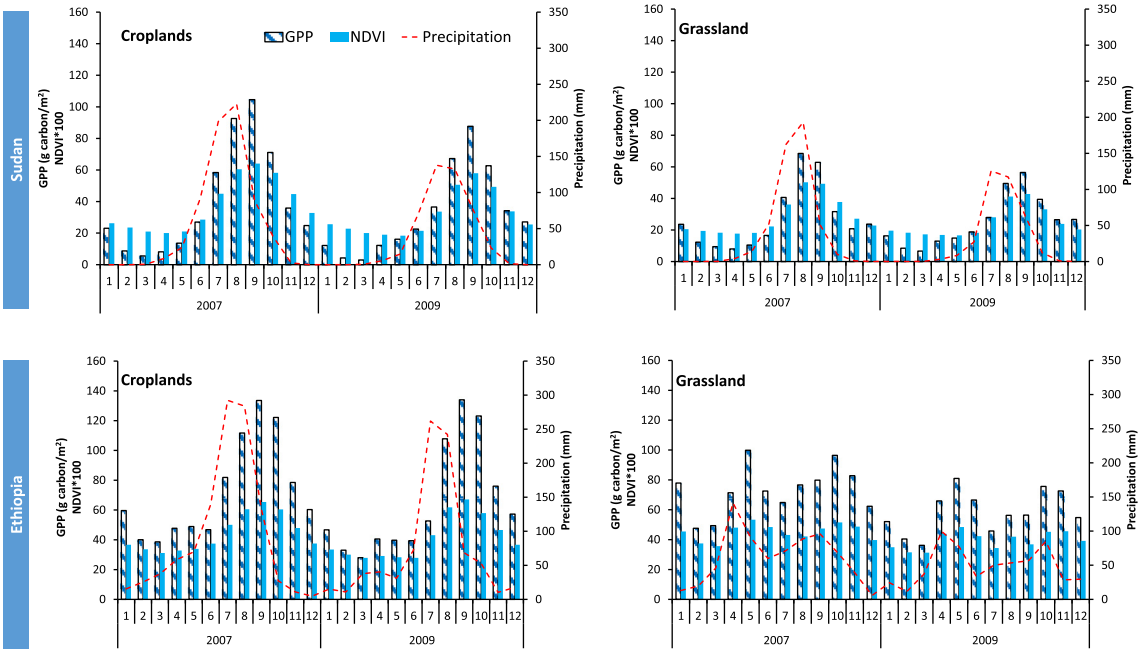

Fig. 9. Monthly GPP, NDVI and precipitation during the wet year 2007 and the dry 2009 for croplands and grasslands in the two countries.

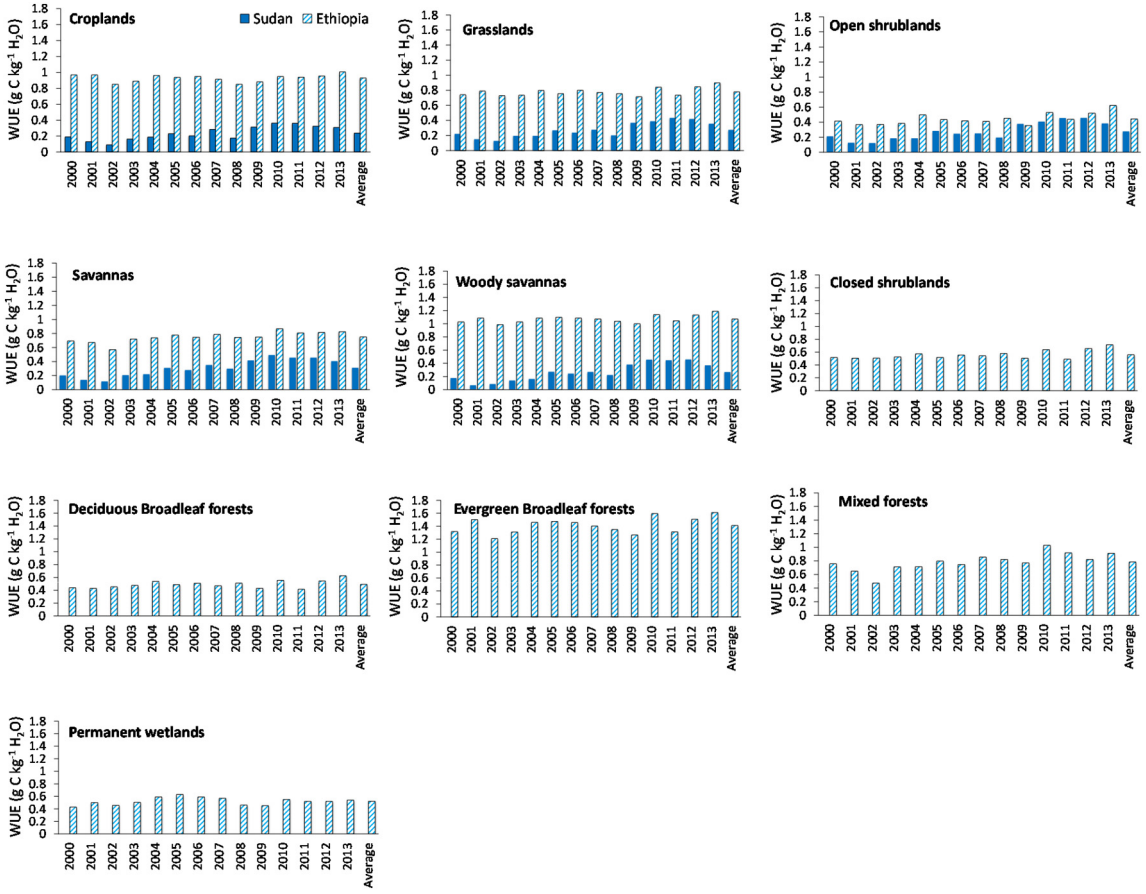

Fig. 10. Time series of WUE of the land cover types in Sudan and Ethiopia.

region. Open shrublands show the lowest CUE among all land covers, giving annual CUE of 0.27 and 0.35, respectively for Sudan and Ethiopia. The inter-annual variation in CUE in Sudan's land covers show insignificant correlation with drought (Fig. S7) whereas the land covers in Ethiopia reveal positive correlation between the two variables, giving highest Spearman's ρ values with SPEI1 and SPEI03 for most land covers (Fig. S8). These local-scale results support the previous global-scale findings by Zhang et al. (2009) and DeLucia et al. (2007).

The multi-year average of CUE is about 0.50 for Ethiopia which is close to the global average of 0.52 (Zhang et al., 2009), and within the realistic range of CUE for Africa, i.e. 0.45 to 0.60 (Amthor, 2000). In contrast, the average CUE for Sudan (0.31) is much lower than both the global and the continental averages. This result indicates higher respiration from the land cover types in Sudan compared to the same land cover types in Ethiopia. One of the major conclusions of these findings is that future climate change might impact the efficiency of land cover types as sinks for atmospheric carbon by affecting carbon sequestration capacity (Xiao et al., 2013). However, large uncertainty is expected in estimating CUE for Africa because of uncertainties in estimating vegetation productivity in the continent in addition to the relatively small amount of field measurements in comparison with other continents (Ardö, 2015; Valentini et al., 2014).

3.8. Implications of the results to food security and climate change

The decrease in NPP may increase global warming (Zhao and Running, 2010) and have the potential to affect food security. NPP is a main indicator of food production. The ability/efficiency of plants to assimilate atmospheric CO_2 and convert it into biomass is of supreme importance for food production. Increasing this ability/efficiency will consequently increase crop yield. Cereals are the main staple crops in the region. Both countries are facing gaps between the demand for and supply of these crops. Any reduction in the current yield (in kilogram/hectare) of the cereal crops in Sudan and Ethiopia or the cultivated area would widen this gap and, consequently, jeopardize food security in these countries. Drought may affect crop yield and may have a negative impact on the suitability of rainfed agriculture. According to data from the Food and Agriculture Organization of the United Nations (FAOSTAT, 2017) for many years within our investigation period, a decrease in cereal crop yield and in cultivated area was detected. For instance, the dry year of 2002 witnessed a reduction in cereal yields and the cultivated area decreased as compared to the multi-year averages for the period 2000–2013. This reduction is comparable to the decrease in NPP in croplands in 2002 in both countries. Consequently, a drop in the total production of cereal crops by 25.6% and 33.9% in Sudan and Ethiopia, respectively, was deduced from the FAOSTAT (2017) data. To analyze cause and effect relationships of drought and crop yield, a more in-depth analysis is needed. Crop models, such as WEAP-MABIA (Jabloun and Sahli, 2012), AquaCrop (Vanuytrecht et al., 2014) and Cropsyst (Stöckle et al., 2003), are very useful for such an analysis. Analyzing the relationship of drought and cultivated area of rainfed agriculture could provide an indication on the importance of drought on farmers' decisions to cultivate. Reducing the risk of crop failure due to drought is not only economically essential to farmers but also to improve the food security for the population at large.

From a climate change perspective, vegetation is an important sink for atmospheric CO_2. High CUE of a land cover type means that vegetation in this land cover type is more efficient in assimilating CO_2 and reducing the CO_2 in the atmosphere. Accordingly, the land cover types in Sudan are less efficient than those found in Ethiopia. The findings of the CUE analysis shown here emphasize the importance of some natural vegetation types, such as permanent wetlands, evergreen broadleaf

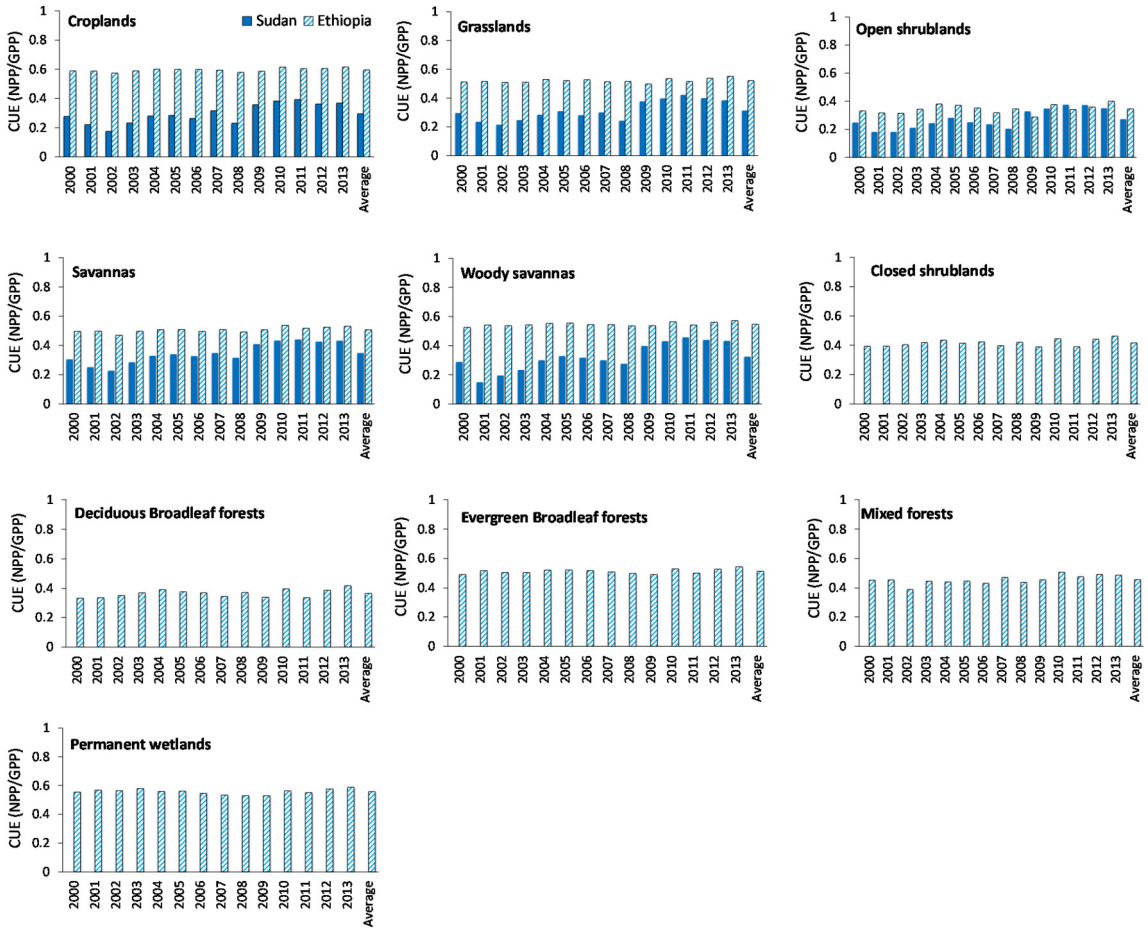

Fig. 11. Time series of CUE of the land cover types in Sudan and Ethiopia.

forests savannah and woody savannah, in mitigating climate change. Especially in Ethiopia, these land cover types exhibit high CUE values. The noticeable increase in CUE in all land cover types in Sudan during the last years of the study period is a positive sign of an enhancement of their efficiency. Against the background of climate change, protecting these land cover types is rather important. Also, the impact of land cover changes should be addressed since this process is responsible for a large share of global greenhouse gases emissions (Smith et al., 2014). Converting natural land into cultivated lands to ensure food security should be carefully evaluated in light of the sustainability goals and adverse consequences such as land degradation and climate change. Increasing WUE and CUE of the existing croplands, especially in developing countries, is crucial to increase food production while maintaining the sustainability of natural resources and mitigating climate change. Our results indicate ample potential to increase WUE and CUE and thus to increase food production in Sudan and Ethiopia without expanding cropland.

To conclude, understanding how NPP responds to climate variability can help develop measures of more efficient management of these land covers. This can significantly contribute to securing food and at the same time reducing the impacts of climate change. Improved landuse management and utilizing the potential arising from improved WUE and CUE is crucial in strengthening the ability of Sudan and Ethiopia to address food security and adapt to climate change.

4. Limitation and uncertainty

Public-domain data based on remote sensing and models can provide an improved understanding of the spatial and temporal patterns of primary productivity and climate, especially in data-scarce regions. Nevertheless, all data have inaccuracy and uncertainty. One major drawback of using these data in the current research was the lack of ground-based data of NPP, WUE and CUE to validate the findings. All of the studies reviewed so far, however, note this as the greatest challenged.

MOD17 NPP data come with quality control dataset (QC), where QC is measured in percentage of the number of days with poor quality of data (due to clouds) from the total number of days in the growing season. In MOD17 algorithm, the data with poor quality are artificially filled with Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) and Leaf Area index (LAI); thus, higher QC values represent lower quality (Ardö, 2015). In the current research, processing of these QC data for the study area revealed lower QC values for most land cover types in Sudan (Fig. 12) because Sudan is drier than Ethiopia and, hence, with less cloud frequency. From the producers point of view, this suggests a better input data quality to generate the MOD17 NPP product for Sudan than for Ethiopia. Evergreen broadleaf forests in Ethiopia represent the land cover with the least reliable data (QC of about 58% of days). Open shrublands exhibited the best QC for both countries because they are located mostly in areas with low precipitation and less occurrence of cloud; hence, their NPP data could be considered more reliable in comparison with those for other land cover types. The overall mean QC is 24% for Sudan and 32% for Ethiopia.

Accurate precipitation data is of prime importance to this study; thus, a critical review of the accuracy of the precipitation products based upon a literature review is essential. There are many public-domain precipitation products available online. According to the literature, these products have different accuracies and their performance can be quite different. Generally, the overall accuracy of remote sensing precipitation estimations in water balance studies is about 82% (Karimi and

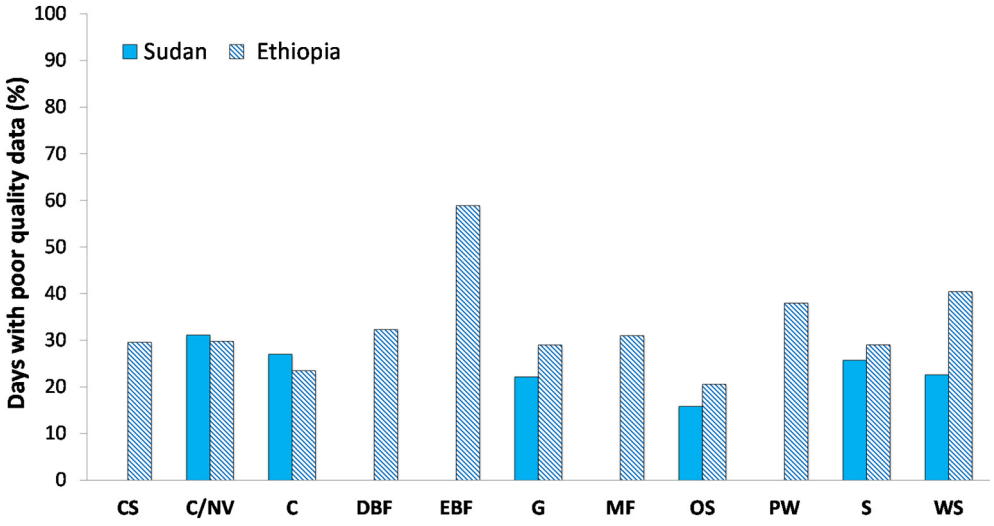

Fig. 12. Quality control of NPP data for each land cover in Sudan and Ethiopia.

Bastiaanssen, 2015). Many studies were conducted to test the performance of CHIRPS along with other public-domain precipitation products in different regions in Sudan and Ethiopia. According to Funk et al. (2015), CHIRPS exhibits the lowest bias as compared to other products. The higher accuracy is, in part, due to using ground station data in producing this precipitation product. CHIRPS shows the highest Pearson correlation coefficient of 0.61–0.79 and the lowest bias and mean absolute error when compared with ground station data (Bayissa et al., 2017). A mean error of about −27.9 mm in some locations in the study area is found by Bayissa et al. (2017) to be quite low compared to that obtained for other products.

Tang et al. (2014) found that WUE calculated on global scale using remote sensing data is consistent with tower measurements. However, calculating WUE and CUE using public-domain data may involve a high degree of uncertainty. Lack of ground data with good spatial coverage makes it impossible to validate the regional WUE and CUE estimates for this study. The currently available data are suitable only for analyzing the NPP, WUE and CUE for various land cover types but not for plant species. It will be useful to detect the NPP, WUE and CUE across species if more detailed data are available. Results from this analysis should be interpreted with caution though, as the relationship between primary productivity and climate variability only hold if other factors remain constant (e.g., management, technology and crop variety).

Nevertheless, these datasets are very valuable to understand the spatial and temporal patterns of the NPP, WUE and CUE of land cover types in data-scarce areas like the region of Sub-Sharan Africa. In addition, they enable the investigation of the relationship between land cover and climate processes, a type of information that is otherwise unavailable for many areas around the world. Such understanding, in turn, is useful to understand the interactions of land use, land cover and ecosystem management.

5. Conclusions

In this study, we have provided new insights into the interaction between land cover types and climate in two countries in Sub-Saharan Africa. Results of the current research confirm that NPP responds differently for different land cover types and for the same land cover types located in different climate conditions. The variation of NPP in the region is primarily driven by climate variation. The last few years of the study period (2009–2013) showed positive NPP anomalies in all vegetation land cover types in Sudan. This was mainly induced by the recent recovery of precipitation. The current analysis revealed that a moderate drought, such as that of 2009, can lead to reduced annual NPP, and vice versa for a wet year (e.g. 2007). Drought decreases the growing season iNDVI of the croplands and grasslands remarkably in both countries. Low iNDVI reflects low productivity and results in negative effects on food production.

There is a strong positive correlation between the inter-annual variability of NPP and drought severity of three months SPEI03 in most of the vegetation land cover types in Ethiopia, but no statistically significant correlation was found between the two indices for Sudan. This suggests that land cover types in Sudan are more resistant to drought than those present in Ethiopia. In Ethiopia, savannah are the most sensitive land cover to drought in the time step of three months while croplands and permanent wetlands are the least sensitive land cover types.

Analysis of WUE and CUE is often performed for short time periods and for individual plants or small plots (Zhang et al., 2009). However, this study has offered spatio-temporal analysis of both indicators. The results of this analysis showed that all land cover types in Ethiopia have higher WUE and CUE than their counterparts in Sudan, thus reflecting the prevalent climate conditions in each country. WUE and CUE display differences in magnitude among the land cover types. They also respond differently to climate conditions and drought severity. Despite the limitation and uncertainty encountered in using public-domain data, the current study provided insight into using these data for monitoring and analyzing NPP, WUE and CUE and their interaction with climate variables on a country scale. Moreover, this analysis has provided an essential understanding of the interactions between ecosystem productivity and efficiency and climate variability. The findings of the current research could be considered as a basis for further analysis of the impact of climate variability on food production. They also provide essential information for the critical role some land cover types play as sinks for atmospheric carbon and, therefore, for climate change studies.

Competing interests

The authors declare no competing interests.

Acknowledgement

We are grateful for the Center for Natural Resources Development (CNRD) and the Deutscher Akademischer Austauschdienst (DAAD) for the PhD scholarship awarded to the first author. The authors thank the projects of MOD16, MOD17, FEWS NET, UDel, CHIRPS, SPEI, and MCD12Q1 for offering the datasets used in the current study through their public dissemination websites. We would like to thank the

reviewers for constructive remarks and suggestions, which helped us to improve the manuscript significantly.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2017.12.090.

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